ISSN 1440-771X

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May 2005

Working Paper 11/05

Is systematic downside beta risk really priced? Evidence in emerging market data

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Abstract

Several studies advocating safety first as a major concern to investors propose downside beta risk as an alternative to the traditional systematic risk- beta. Downside measures are concerned with a subset of the data and therefore the results in the studies that consider the downside beta only may be biased. This study addresses this issue by including downside co-skewness risk in addition to the downside beta risk in the pricing model. In a sample of 27 emerging markets two-stage rolling regression analysis fail to support pricing models with downside risk measures. In a cross-sectional analysis inclusion of downside co-skewness improves model fit. When considered together, downside beta is potential and downside co-skewness is a risk to the rational investor. Even though our results are inconclusive the evidence strongly suggests a need for further investigation of co-skewness risk in pricing models that adopt a downside risk framework.

JEL Codes: G12, G15

Keywords: Beta, Downside risk, Emerging markets

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1. Introduction

The capital asset pricing model (CAPM) due to Sharpe (1964) conveys the notion that securities are priced so that their expected return will compensate investors for their expected risk. Though the CAPM beta is still one of the most commonly used measures of security price movement researchers have strongly questioned the empirical validity of the assumptions underlying its derivation. In the mean-variance framework which the CAPM is built on, variance identifies extreme gains as well as extreme losses as undesirable. Advocating safety first as the major concern of rational investors some argue that only downside risk may be relevant to an investor. A number of studies investigated downside risk as a measure of security risk. First the concept of semi-variance that makes reference to a benchmark return emerged and later several downside risk measures based on the semi-variance framework emerged. When computing downside risk only a subset of the return distribution is used and minimization of the semi-variance concentrates only on the reduction of losses. Further, the semi-variance is applicable only when portfolio return distribution is non-symmetrical. When the portfolio return is normally distributed semi-variance below the expected return is half the portfolio's variance and hence variance may still be used to quantify risk. Nantell and Price (1979) show analytically that under the assumption of bivariate normal distribution of returns for an asset and the market, equilibrium rates of return are equal whether we use a variance or semi-variance notion of portfolio risk.

Downside beta is both intuitively and theoretically appealing, and empirically can provide a better risk measure than the regular beta (Post and van Vliet, 2004). Hogan and Warren (1974) in a theoretical framework and Jahankhani (1976) in an empirical study compared mean-variance and mean-semivariance pricing models and observed no difference in the two models in terms of linear association between expected return and beta. Estrada (2002) reveals that downside risk measures excel over the standard risk measures in explaining variability in the cross-section of returns in emerging markets. Pederson and Hwang (2003) in an investigation of UK equity data show that even though the downside beta explains a proportion of equities in addition to CAPM beta the proportion of equities benefiting from using the downside beta is not large enough to improve asset pricing models significantly. Ang, Chen, and Xing (2002) find a similar result in the US market. Ang, Chen and Xing (2002) measured downside risk by correlations conditional on downside moves of the market. They observed that the portfolio of stocks with the greatest downside correlations outperforms the portfolio of stocks with the lowest downside correlations and that this effect cannot be explained by the Fama and French (1993) model.

Downside risk is appropriate when the security returns distribution is skewed. This raises another question. When the skewness of an asset return distribution is negative the downside returns will have a larger magnitude of returns than the upside returns. In other words, losses when they occur will tend to be large. Therefore rational investors dislike securities with negative co-skewness with the market portfolio returns so that securities with low co-skewness tend to have high average returns. When the skewness of the security returns distribution is positive, the upside returns will have a larger magnitude of returns than the downside returns. Therefore when losses (gains) occur they will be smaller (greater). Hence investors prefer positively skewed markets and will be willing to pay a premium for positive co-skewness. Therefore the questions that arise is whether co-skewness need be considered as a measure of risk in a mean semi-variance framework and how it should be measured and interpreted.

Downside beta is explicitly conditional on market downside movements. On the other hand the traditional co-skewness measure does not explicitly accentuate asymmetries across up and down markets. This makes interpretation of co-skewness measures defined in a downside framework difficult. This study addresses this issue using emerging market data. We consider three downside beta risk measures: Estrada beta (E-beta), Hogan and Warren beta (HW-beta) and Bawa and Lindenberg beta (BL-beta). We define the co-skewness counterparts of these downside beta risk measures and investigate whether downside beta and downside co-skewness are useful in explaining the cross-section of expected returns. Our results reveal that when the CAPM beta or any of the three downside betas only is included in the pricing model the risk premium associated with it is positive and only the E-beta is statistically significant. However, E-beta and CAPM beta together fail to explain the cross-section of expected returns. When downside co-skewness is included in addition to the corresponding downside beta risk the risk premium associated with the beta (co-skewness) risk is negative (positive). This is observed only with the Hogan-Warren and Bawa-Lindenberg measures. When the CAPM beta is included in the pricing model the evidence is even stronger. Hogan-Warren measures outperform the Bawa-Lindenberg measures in explaining cross-section of expected returns.

The paper is organized as follows. The downside risk measures are defined in the next section followed by hypotheses of interest. Thereafter the methodology and the data are described in that order. The results and their discussion follow next. The paper is concluded with some remarks.

2. Downside risk measures

Estrada (2002) defined an asset *i*'s covariance with market portfolio in a downside framework as $S_{im}^{(E)} = E\left[\min\{(R_i - \mu_i),0\}\min\{(R_m - \mu_m),0\}\right]$ leading to a measure of systematic downside risk, the E-beta, given by

$$\beta_{im}^{(E)} = \frac{E\left[\min\{(R_i - \mu_i),0\}\min\{(R_m - \mu_m),0\}\right]}{E\left\{\left[\min(R_m - \mu_m),0\right]^2\right\}}. \tag{1}$$

Following the rationale of including only the returns below the respective means in the measurement of risk, the downside co-skewness (E-gamma) risk may be defined as

$$\gamma_{im}^{(E)} = \frac{E\left[\min\{(R_i - \mu_i),0\}\left[\min\{(R_m - \mu_m),0\}\right]^2\right]}{E\left\{\left[\min\{(R_m - \mu_m),0\}\right]^3\right\}}. \tag{2}$$

Hogan and Warren (1974) in the development of their expected value-semi-variance model defined the co-semi-variance as $S_{im}^{(HW)} = E\left\{\left(R_i - R_f\right)\min\left(R_m - R_f, 0\right)\right\}$. The downside beta

(HW-beta) and the downside gamma (HW-gamma) corresponding to the Hogan and Warren (1974) definition of co-semi-variance can be given as

$$\beta_{im}^{(HW)} = \frac{E\left\{\left(R_i - R_f\right)\min\left(R_m - R_f, 0\right)\right\}}{E\left\{\left[\min\left(R_m - R_f, 0\right)\right]^2\right\}} \tag{3}$$

and

$$\gamma_{im}^{(HW)} = \frac{E\left\{\left(R_i - R_f\right)\left[\min\left(R_m - R_f, 0\right)\right]^2\right\}}{E\left\{\left[\min\left(R_m - R_f, 0\right)\right]^3\right\}}. \tag{4}$$

Bawa and Lindenberg (1977) suggested the use of the mean return instead of the risk-free rate in (3). In this case the expression for the downside beta (BL-beta) becomes

$$\beta_{im}^{(BL)} = \frac{Cov\left(r_i, r_m \middle| r_m < \mu_m\right)}{Var\left(r_m \middle| r_m < \mu_m\right)} \tag{5}$$

where r_i $\left(r_m\right)$ is security i's (the market's) excess return and μ_m is the average excess market return. The corresponding downside gamma risk (BL-gamma) may be expressed as

$$\gamma_{im}^{(BL)} = \frac{E\left\{\left(R_i - \mu_i\right)\left[\min\left(R_m - \mu_m, 0\right)\right]^2\right\}}{E\left\{\left[\min\left(R_m - \mu_m, 0\right)\right]^3\right\}}. \tag{6}$$

3. Hypotheses of interest

It is clear in (1) that a security contributes to the downside beta risk, $\beta_{im}^{(E)}$ only when $R_i < \mu_i$ and $R_m < \mu_m$ for which a premium is sought by a rational investor. Further, when $R_i < \mu_i$ and $R_m < \mu_m$, a security also contributes to the downside gamma $\gamma_{im}^{(E)}$. Further, downside risk measures are appropriate when returns distribution is skewed and therefore if only downside beta is considered in asset pricing models we could get biased results. In the conventional sense co-skewness is preferred by a rational investor in a negatively skewed market and hence they would be willing to forego expected return. Hence in a downside framework the beta and gamma are likely to have differing influence on the expected return.[1]

Estrada (2002) reported empirical results to support the downside CAPM given as $E(R_i) = R_f + MRP_b \beta_{im}^{(E)}$, where MRP_b is the downside market beta-risk premium. Now to incorporate downside gamma risk in an asset pricing framework we extend the downside CAPM model as

$$E(R_i) = R_f + MRP_b \beta_{im}^{(E)} + MRP_g \gamma_{im}^{(E)} \tag{7}$$

where MRP_g is the market risk premium associated with the downside gamma-risk. In this case we expect MRP_b and MRP_g to have opposite signs.

In the Hogan-Warren definition a security adds to the beta risk, $\beta_{im}^{(HW)}$ and gamma risk, $\gamma_{im}^{(HW)}$ only when $R_m < R_f$. In this case gains in the market are not included in the measurement of risk and therefore account for only the returns on a falling market. According to (3), in a falling market a security adds to the downside beta risk when $R_i < R_f$ and reduces the downside beta risk when $R_i > R_f$. Therefore the interpretation of beta risk is not clear and hence the contribution of the associated market risk premium on the expected asset return is not clear either. The downside gamma risk poses a similar problem. That is when $R_i < R_f$ $(R_i > R_f)$ a security enhances (reduces) $\gamma_{im}^{(HW)}$ risk in a falling market. The same argument holds in the case with the Bawa-Lindenberg risk measures the difference being the risk-free rate is now replaced by the appropriate mean. Even though it is not clear what signs should be expected in the HW-beta (BL-beta) and HW-gamma (BL-gamma) risk premiums the fact that both beta and gamma risk

[1] The multi-moment models are not sufficiently flexible to model downside risk and it is generally difficult to restrict these models to obey the standard regularity conditions of nonsatiation (no-arbitrage) and risk aversion (Post and van Vliet, 2004).

increases or decreases depending on whether the security return exceeds the mean (risk-free rate) or not suggests that their risk premiums are likely to have opposite signs.

4. Methodology

4.1 Cross-sectional analysis

First, for each market we estimate the systematic risks and average return using the full set of sample data. The average return is then regressed on the estimated systematic risk/s to investigate whether or not the corresponding risk-return linear relationships are significant.[2]

4.2 Two-stage rolling regression analysis

We investigate the risk-return relationships allowing for systematic risks to vary over time. The analysis here is based on a two-stage procedure. In the first stage we estimate systematic risks using the method of ordinary least squares and with time series data. We start the procedure by estimating for each market the systematic risks using the data corresponding to the first 60-month period. In the second stage adopting the method of cross-sectional regression we test whether the systematic risks are priced or not. In each of the 12 months that follows the 60-month period used in the first stage, the monthly market returns are regressed on the systematic risks estimated in the preceding 60-month period. Here, it is assumed that the systematic risks estimated in the first stage proxy systematic risks of the second stage.[3] The two-stage procedure is then repeated using a rolling window technique, rolling forward 12 months at a time.

[2] The sample data for all markets do not have the same start date. Therefore, we repeat the analysis with a shorter time period so that for each market the average return and the systematic risk/s is estimated with data in the same period.

[3] Co-variances are measured with error and measurement error reduces the statistical power of any regression. One way of circumventing the measurement problem is to focus on a setting where the true variation in the data is large relative to any noise (Chari and Henry, 2004). Inclusion of downside gamma risk in the pricing model is expected, at least partially, to alleviate this concern.

There are three different start dates in the sample data. Therefore to accommodate all the 27 markets in the two-stage rolling regression analysis we use a truncated data set. This allows five repetitions of the two-stage procedure enabling estimation of systematic risk premiums in 60 consecutive months.

5. Data

The data used here is from the MSCI database on emerging market monthly indices. We consider 27 markets- 10 Asian, 7 Latin American and 10 African, Middle-Eastern and European. The sample period varies where for 12 markets the start date is January 1987, for 10 markets it is January 1992 and for the rest the start date is January 1994. For all markets the data is collected up to December 2004. The returns are computed as the difference in two consecutive monthly log prices.[4] The proxy used for the market index is the world index available in the MSCI database and the proxy for the risk-free rate is the 10-year US Treasury bond rate.[5]

The complete list of the markets, the data start dates and some summary statistics is given in Table 1. Entries in Table 1 reveal that for markets, the minimum return ranges from –110.8 percent to –15.1 percent while the maximum varies between 78.1 percent and 15.6 percent.

[4] A study (Estrada, 2002) using a data set comparable to ours examined asset pricing models with downside beta with return computed as the arithmetic return. Therefore to compare our results to the results in that study we repeat the analysis with arithmetic returns.

[5] If a market is not liberalized the relevant source of systematic risk for pricing stocks is the local stock market index. When a country's stock market is liberalized the source of systematic risk of an asset becomes the world market portfolio. The sample data for all countries is in the post liberalization era and hence the reason for using world index. We examine the robustness of our results with equal-weighted average return of all the 27 markets as a proxy for the world market portfolio return and the US 3-month Treasury bill rate as the risk-free rate.

Excess kurtosis can be as high as 9.3 with the minimum being –0.4. Excess kurtosis is positive in eleven markets. The skewness ranges from –1.4 to 0.9 with eight markets with positive skew. The world market return distribution is negatively skewed and has 0.7 excess kurtosis and 0.5 percent mean return.

6. Results and discussion

6.1 Cross-sectional models

First, we estimate the following cross-sectional regression models.

Model A: (includes the CAPM beta)

$$E(R_i) = R_f + MRP_b \beta_{im}, \tag{8}$$

Model B (includes E-beta)

$$E(R_i) = R_f + MRP_b^E \beta_{im}^{(E)}, \tag{9}$$

Model C (includes E-beta and E-gamma)

$$E(R_i) = R_f + MRP_b^E \beta_{im}^{(E)} + MRP_g^E \gamma_{im}^{(E)}, \tag{10}$$

Model D (includes HW-beta)

$$E(R_i) = R_f + MRP_b^{HW} \beta_{im}^{(HW)} \tag{11}$$

Model E (includes HW-beta and HW-gamma)

$$E(R_i) = R_f + MRP_b^{HW} \beta_{im}^{(HW)} + MRP_g^{HW} \gamma_{im}^{(HW)}. \tag{12}$$

and

Model F (includes E-beta and HW-beta)

$$E(R_i) = R_f + MRP_b^E \beta_{im}^{(E)} + MRP_b^{HW} \beta_{im}^{(HW)} \tag{13}$$

The results reported in Table 2 give the parameters estimated in the above models where for each market the mean return and the risk measures are estimated using the full set of sampled data.[6] The data does not support the traditional CAPM model. The estimates shown in panel 2 reveals weak support (significant at the 10 percent level) for the Estrada downside CAPM model with a positive premium however when the downside gamma risk is included in the model (Model C) both E-beta and E-gamma are not significantly different from zero. The results in Model D reveal that the premiums associated with the HW-beta and BL-beta risk measures are not significant. However, when the gamma risk is included (Model E) the premiums corresponding to downside beta and downside gamma are significant at the five percent level when Hogan-Warren measures are used and at the five and ten percent levels respectively when Bawa-Lindenberg measures are used. Further, the two premiums have opposite signs with a negative premium for downside beta risk. We also estimate a model (Model F) where both the E-beta and the HW-beta is included in the pricing model. In this case both risks tend to be priced with a positive premium for E-beta risk and a negative premium for HW-beta risk. When the risk-free rate in the HW-beta measure is replaced with the appropriate mean only the Estrada beta risk premium is priced with a positive sign and at the ten percent level.

In general, as far as the sign of the risk premium is concerned, whenever the CAPM beta or any of the three downside betas is included in the pricing model separately the risk premium associated with it is always positive.[7] On the other hand, when the gamma is included in addition to the corresponding beta risk the risk premium associated with the beta (gamma) risk is negative (positive).[8] The R-square/adjusted R-square values indicate that the fit in these models is very

[6] The correlation between the estimated $\beta_{im}, \beta_{im}^{(E)}, \gamma_{im}^{(E)}, \beta_{im}^{(HW)}$ and $\gamma_{im}^{(HW)}$ is very high. This is addressed under further testing when robustness of the results is discussed. The variation in market returns is rather small and therefore heteroscedasticity is not a concern here.

[7] In some instances the risk premium is not significantly different from zero.

[8] In some instances the risk premium is not significantly different from zero.

poor. The best fit is revealed in Model F with an adjusted R-square value of less than nineteen percent.

Now we discuss the results when the CAPM beta is included in models A–F. These results are given in Table 3. The results in the first panel of Table 3 reveals that when the pricing model (Model AA) includes the CAPM beta risk together with E-beta none of them is priced and the model has a very poor fit. A similar result is obtained in Model BB where the CAPM beta, E-beta and E-gamma are present. When the HW-beta together with the CAPM beta is in the model (Model CC) both risks are priced with investors demanding a premium for the beta risk and willing to forego expected return for the downside beta risk.[9] When the CAPM beta and the BL-beta are considered none of the corresponding risk premia are significant. On the other hand, when Model CC is enhanced with the gamma risk (Model DD) all three risks are priced with investors requiring a premium for the CAPM beta risk as well as the gamma risk and willing to pay a premium for the downside beta risk. This is observed whether or not the excess return in the downside framework is based on the risk-free rate or the mean return. This together with the result in Model E given in Table 2 suggests that when downside beta and downside gamma are present together in the pricing model investors display a preference for downside co-skewness and dislike downside beta risk. The presence of the CAPM beta in the pricing model makes these observations even stronger (adjusted R-square increases from 17 percent to 42 percent).

Earlier we observed in Model F, Table 2 that when the E-beta and HW-beta are in the model their associated risk premiums are priced with investors displaying a preference for the Hogan-Warren downside risk and dislike for E-beta risk. Model EE where Model F is extended to

[9] Pederson and Hwang (2003) using UK equity data show that even though the downside beta explains a proportion of equities in addition to CAPM beta the proportion of equities benefiting from using the downside beta is not large enough to improve asset pricing models significantly. Their results show that downside betas are of limited use in asset pricing compared to CAPM beta.

include the CAPM beta reveals a similar result with a better model fit (adjusted R-square increases from 18 percent to 38 percent) with a positive and significant CAPM beta risk premium. In general, inclusion of the CAPM beta in the pricing model with downside risk measures improves model fit and the signs of the risk premium observed in the pricing model without the CAPM beta are preserved. Downside risk measures due to Hogan and Warren seems more appropriate than Bawa-Lindenberg measures when the CAPM beta is in the pricing model.

We also investigate the association between the mean return and risk when the 27 markets are divided into three equally-weighted portfolios ranked on CAPM beta, E-beta, HW-beta, E-beta and E-gamma and HW-beta and HW-gamma. If the systematic component of a given risk is priced then stocks sorted by the relevant measure of risk should exhibit cross-sectional spreads in expected returns. The first portfolio (P1) consists of the markets with the lowest nine risk estimates and the third portfolio (P3) consist of the markets with the highest nine risk estimates. The results reported in Table 4 reveals that the average return in P1 lies between that of P2 and P3 when the portfolios are formed on the CAPM beta and the E-beta of the market. This is an unexpected result especially when portfolios are formed on the CAPM beta. On the other hand the average portfolio return appears to increase with increasing HW and BL portfolio beta suggesting that the relationship between E-beta and return may not be monotonically increasing. This may be one of the reasons why the sample data do not support the pricing models that include E-beta and E-gamma. When portfolios are formed on downside beta and downside gamma a monotonically increasing average return-risk relationship is observed only with BL measures of risk when excess return is computed with reference to the mean return.

6.2 Rolling regression

Note that the two-stage rolling regression analysis is carried out with a reduced sample and the model parameters are estimated in 60 cross-sectional regressions. The models estimated here are A-E described in Table 2. The results (not shown) reveal that none of the pricing models are supported. This result does not change when the pricing models are tested in each of the five rolling window periods separately. We repeated the portfolio analysis with the reduced sample as well. Here the average return in P2 is negative while the average return in P1 and P3 are positive with P3 having a higher average irrespective of the risk measure used in forming the portfolios. The results are reported in Table 5.

6.3 Robustness of the results

6.3.1 Market return

We repeated the cross-sectional and the rolling regression analysis with the equally-weighted return of the 27 sampled markets as the market return. The results are largely unchanged from those obtained with world index return as a proxy for the market portfolio return. When the US 10-year Treasury bond rate is replaced with the US 3-month Treasury bill rate there is no notable change in the results.

6.3.2 Arithmetic returns

Estrada (2002) in a study of the same set of emerging markets that we sampled found strong empirical evidence to support the E-beta against the CAPM beta when arithmetic market returns are used.[10] In our data set the summary statistics with arithmetic returns, which we do not report for the sake of brevity, clearly indicates an increase in average monthly return (from 0.64 percent to 1.32 percent), average skew (from -0.20 percent to 0.53 percent) and average excess kurtosis

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[10] In arithmetic (discrete) returns a percentage gain followed by the same percentage loss in two consecutive periods does not revert back to the original investment whereas in log (continuously compounded) returns such a move does. Even though returns are considered to be generated continuously through time sometimes returns are treated as if they are generated at discrete intervals due to trading that occur at discrete intervals. See Brailsford, Faff and Oliver (1997) for a detailed discussion on this issue.

(from 2.68 percent to 3.30 percent) from those calculated with the log returns. In view of this variation we investigate the sensitivity of our results when the market return is computed as an arithmetic return.

The results in the cross sectional regression analysis reported in Table 6 reveals that when CAPM beta, E-beta, HW-beta and BL-beta are considered separately in a pricing equation the investors require a premium that is significantly different from zero to accept the corresponding risk. In log returns statistical evidence is found only with E-beta. When E-gamma is included with E-beta in the same model none of the associated risks are priced. This was uncovered in the log returns as well. On the other hand, when HW-gamma is included in the pricing model together with HW-beta the risk premium associated with both risks are priced where a preference for the HW-beta (BL-beta) risk and an aversion for the HW-gamma (BL-gamma) risk is noted. A similar observation is made in log returns. When E-beta and HW-beta both are in the pricing model the model fit improves and they are both priced such that E-beta has a positive risk premium and HW-beta (BL-beta) has a negative risk premium.

When we construct portfolios and examine the average portfolio return against portfolio risk we find that the CAPM beta and return and HW-beta and return have a positive relationship. The results in Table 7 also reveal a positive relationship between portfolio risk and return when portfolios are formed by ranking the markets on HW-beta and HW-gamma. With Estrada measures P2 (0.947 percent) has a slightly lower return than P1 (0.951 percent) and P3 has a much higher return (2.056 percent) than P1. The composition of portfolios does not change when E-gamma is also used in the ranking. Consequently the returns in portfolios formed on ranked ES-beta and ranked E-beta and E-gamma are the same. A similar observation is made in Tables 4 and 6 when log return in the full sample and a truncated sample is used. This may be the reason why we failed to find evidence in support of E-gamma in any of the models considered. Besides the presence of E-gamma in the pricing model makes the risk premium associated with E-beta insignificant. In arithmetic returns the spread between P1 and P3 is larger than in log returns.

6.3.3 Further testing

We observe high correlation between CAPM beta, downside beta and downside gamma where the Pearson correlation coefficient exceeds 0.9. Hence we conduct further tests to determine whether or not downside beta and downside gamma is priced when the CAPM beta is in the pricing model. First downside beta is regressed on a constant and CAPM beta. The residuals from this regression which are orthogonal to CAPM beta are effectively the orthogonalised component of downside beta. Thereafter expected returns are regressed on CAPM beta and orthogonalised downside beta. The results of the analysis are shown in Table 8.

The results in Table 8 indicate that the orthogonalised component of E-beta and BL-beta is not significant. This suggests that E-beta and BL-beta may not be useful in explaining cross-section of asset returns when the CAPM beta is in the pricing model. On the other hand, the orthogonalised component of HW-beta is significant at the 1 percent level. Hence our results provide some backing for inclusion of HW-beta in the pricing model in addition to the CAPM beta. A similar observation was made in model CC whose results are shown in Table 3.

Further, model DD whose results are shown in Table 3 reveals that HW-gamma together with CAPM beta and HW-beta explains in excess of 42 percent of variation in the cross section of expected returns. We test this result adopting a two step procedure similar to the one used earlier when testing the appropriateness of downside beta in explaining asset prices. Here HW-gamma is regressed on a constant, CAPM beta and HW-beta first. In the second step the cross section of expected returns is regressed on a constant, CAPM beta, HW-beta and the residuals obtained in the first step. The aim is to see whether there remains any unexplained variation in expected returns which HW-gamma may account for in addition to those explained by CAPM beta and HW-beta. The results shown in Table 8 provide evidence in support of the earlier observation that the variation in cross-section of expected return may be explained better by CAPM beta together with HW-beta and HW-gamma.

7. Concluding remarks

In general, when the CAPM beta or any of the three downside betas is included in the pricing model the risk premium associated with it is always positive. On the other hand, when the downside co-skewness is included in addition to the corresponding downside beta risk the risk premium associated with downside beta (downside co-skewness) risk is negative (positive). When the CAPM beta is included in such a pricing model the evidence is even stronger. In this case downside risk measures due to Hogan and Warren are more appropriate than Bawa and Lindenberg measures.

Our results however are inconclusive. Emerging market risk premium may not be determined solely by risk factors common to all countries. A combination of global and local risk factors may influence some markets. Our observations suggest that investigation of downside co-skewness is crucial in understanding asset pricing in a downside framework.

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Table 1. Summary statistics of emerging market monthly log return

Country	Min	Max	Mean	SD	Skew	Kurtosis	Sample start date
Argentina	-48.561	66.965	1.1965	1.0739	0.6283	3.7663	Dec, 87
Brazil	-110.665	59.471	1.1322	1.2008	-1.3745	9.2586	Dec, 87
Chile	-34.401	19.517	1.0965	0.5110	-0.4241	2.1701	Dec, 87
China	-32.395	38.183	-0.9654	0.9300	0.3298	1.4507	Dec, 92
Colombia	-27.586	26.474	0.6038	0.7753	-0.1998	0.8749	Dec, 92
Czech Republic	-32.400	26.298	0.9280	0.7852	-0.5075	1.6929	Dec, 94
Egypt	-15.111	35.077	1.1518	0.7995	0.9056	1.6660	Dec, 94
Hungary	-49.095	37.956	1.5727	0.9593	-0.7860	4.7948	Dec, 94
India	-19.529	19.887	0.4438	0.6968	-0.0665	-0.4175	Dec, 92
Indonesia	-52.473	66.230	0.4446	1.0349	0.4228	4.2320	Dec, 87
Israel	-20.937	23.859	0.3465	0.6502	-0.3647	0.4104	Dec, 92
Jordan	-20.297	15.582	0.3593	0.3325	-0.1156	1.8943	Dec, 87
Korea	-37.478	53.410	0.3584	0.7883	0.3377	3.0023	Dec, 87
Malaysia	-36.115	40.512	0.3925	0.6469	-0.2094	3.5915	Dec, 87
Mexico	-41.951	25.408	1.6112	0.6902	-0.9133	2.8280	Dec, 87
Morocco	-16.489	16.285	0.5655	0.4578	-0.0201	0.9131	Dec, 94
Pakistan	-47.622	31.682	0.0087	0.9653	-0.2692	2.1803	Dec, 92
Peru	-40.983	30.441	0.8522	0.7492	-0.6134	3.5070	Dec, 92
Philippines	-34.653	36.012	0.2272	0.6806	-0.0180	1.6681	Dec, 87
Poland	-42.981	78.065	1.3412	1.1737	0.8257	5.9840	Dec, 92
Russia	-93.068	47.706	1.3207	1.7671	-1.0070	4.2148	Dec, 94
South Africa	-36.881	19.279	0.7267	0.6666	-1.0793	3.4574	Dec, 92
Sri Lanka	-28.975	39.485	0.1136	0.8580	0.3672	1.9743	Dec, 92
Taiwan	-41.047	38.142	0.3957	0.8028	-0.0307	1.1111	Dec, 87
Thailand	-41.632	35.896	0.2777	0.8446	-0.3940	1.7404	Dec, 87
Turkey	-53.177	54.409	0.6106	1.2275	0.0432	0.7000	Dec, 87
Venezuela	-63.767	48.044	0.1840	1.2440	-0.7934	3.7400	Dec, 92

Notes: The returns are expressed as a percentage per month.

Table 2. Cross-sectional analysis of pricing models using log return

Model	λ_0	λ_1	λ_2
Model A: $R_{it} = \lambda_0 + \lambda_1\beta_i + \varepsilon_{it}$			R-square = 0.0948
Mean	0.3206	0.3630	-
Standard error	0.2237	0.2244	-
t-value	1.4333	1.6179	-
Model B: $R_{it} = \lambda_0 + \lambda_1\beta_{im}^{(E)} + \varepsilon_{it}$			R-square = 0.1251
Mean	0.1349	0.3873	-
Standard error	0.2865	0.2049	-
t-value	0.4708	1.8906***	-
Model C: $R_{it} = \lambda_0 + \lambda_1\beta_{im}^{(E)} + \lambda_2\gamma_{im}^{(E)} + \varepsilon_{it}$			Adjusted R-square = 0.0980
Mean	0.2693	-0.7849	1.0583
Standard error	0.3101	1.0806	0.9580
t-value	0.8683	-0.7264	1.1047
Model D: $R_{it} = \lambda_0 + \lambda_1\beta_{im}^{(HW)} + \varepsilon_{it}$			R-square = 0.0394 (0.0647)
Mean	0.4213 (0.3594)	0.2280 (0.2877)	-
Standard error	0.2417 (0.2388)	0.2251 (0.2188)	-
t-value	1.7428*** (1.5052)	1.0130 (1.3145)	-
Model E: $R_{it} = \lambda_0 + \lambda_1\beta_{im}^{(HW)} + \lambda_2\gamma_{im}^{(HW)} + \varepsilon_{it}$			Adjusted R-square = 0.1797 (0.1388)
Mean	0.4323 (0.3814)	-2.1682 (-1.8013)	2.0336 (1.7776)
Standard error	0.2191 (0.2249)	0.9656 (1.0393)	0.8009 (0.8636)
t-value	1.9731** (1.6956***)	-2.2456** (-1.7408***)	2.5391** (2.0584**)
Model F: $R_{it} = \lambda_0 + \lambda_1\beta_{im}^{(E)} + \lambda_2\beta_{im}^{(HW)} + \varepsilon_{it}$			Adjusted R-square = 0.1874 (0.1158)
Mean	-0.0806 (-0.0452)	1.3630 (1.1493)	-1.1008 (-0.8336)
Standard error	0.2914 (0.3139)	0.5253 (0.6139)	0.5509 (0.6343)
t-value	-0.2764 (-0.1440)	2.5950** (1.8720***)	-1.9983** (-1.3143)

Notes: The statistics are based on 27 estimates. The mean and standard error is expressed as a percentage. *** denotes significance at the 10 percent level and ** denotes significance at the 5 percent level. The figures in parentheses are the estimates when the risk-free rate in the Hogan and Warren downside beta and downside gamma (equations (4) and (5)) is replaced with the corresponding mean.

Table 3. Cross-sectional analysis of pricing models with CAPM beta and using log return

Model	λ_0	λ_1	λ_2	λ_3
Model AA: $R_i = \lambda_0 + \lambda_1\beta_{im} + \lambda_2\beta_{im}^{(E)} + \varepsilon_i$				Adj R-sq = 0.0540
Mean	0.1070	-0.1210	0.4904	-
Standard error	0.3196	0.5630	0.5229	-
t-value	0.3349	-0.2150	0.9377	-
Model BB: $R_i = \lambda_0 + \lambda_1\beta_{im} + \lambda_2\beta_{im}^{(E)} + \lambda_3\gamma_{im}^{(E)} + \varepsilon_i$				Adj R-sq = 0.0709
Mean	0.2160	-0.3174	-0.6873	1.2142
Standard error	0.3295	0.5815	1.1112	1.0134
t-value	0.6555	-0.5458	-0.6185	1.1981
Model CC: $R_i = \lambda_0 + \lambda_1\beta_{im} + \lambda_2\beta_{im}^{(HW)} + \varepsilon_i$				Adj R-sq = 0.2374 (0.0594)
Mean	0.5029 (0.3989)	2.6445 (1.3049)	-2.2814 (-0.9297)	-
Standard error	0.2130 (0.2366)	0.8940 (0.9579)	0.8708 (0.9192)	-
t-value	2.3610** (1.6859***)	2.9581* (1.3622)	-2.6198* (-1.0114)	-
Model DD: $R_i = \lambda_0 + \lambda_1\beta_{im} + \lambda_2\beta_{im}^{(HW)} + \lambda_3\gamma_{im}^{(HW)} + \varepsilon_i$				Adj R-sq = 0.4233 (0.1990)
Mean	0.5121 (0.4279)	2.5950 (1.4865)	-4.5739 (-3.3446)	1.9854 (1.9035)
Standard error	0.1853 (0.2187)	0.7776 (0.8876)	1.0840 (1.3583)	0.6717 (0.8362)
t-value	2.7642* (1.9565***)	3.3372* (1.6748***)	-4.2194* (-2.4623**)	2.9557* (2.2763**)
Model EE: $R_i = \lambda_0 + \lambda_1\beta_{im} + \lambda_2\beta_{im}^{(E)} + \lambda_2\beta_{im}^{(HW)} + \varepsilon_i$				Adj R-sq = 0.3800 (0.1569)
Mean	0.0590 (-0.0103)	2.3654 (1.3357)	1.1821 (1.1647)	-3.1691 (-2.0948)
Standard error	0.2591 (0.3075)	0.8135 (0.9071)	0.4630 (0.5996)	0.8587 (1.0570)
t-value	0.2278 (-0.0334)	2.9079* (1.4726)	2.5532** (1.9425***)	-3.6904* (-1.9819**)

Notes: The mean and standard error is expressed as a percentage. *** denotes significance at the 10 percent level and ** denotes significance at the 5 percent level. The figures in parentheses are the estimates when the risk-free rate in the Hogan and Warren downside beta and downside gamma (equations (4) and (5)) is replaced with the corresponding mean.

Table 4. Portfolio (log) return and risk

Portfolio	Markets sorted by β		Markets sorted by $\beta_{im}^{(E)}$		Markets sorted by $\beta_{im}^{(HW)}$	
	β	Return	$\beta_{im}^{(E)}$	Return	$\beta_{im}^{(HW)}$	Return
P1	0.3821	0.5968	0.8000	0.5857	0.4431 (0.4518)	0.5857 (0.5857)
P2	0.8800	0.3305	1.2705	0.4148	0.9706 (0.9967)	0.6472 (0.6472)
P3	1.3827	0.9946	1.8463	0.9213	1.4709 (1.4835)	0.6889 (0.6889)
Spread (P3-P1)	1.0006	0.3978	1.0463	0.3356	1.0278 (1.0316)	0.1033 (0.1033)

Portfolio	Markets sorted by $\beta_{im}^{(E)}$ and by $\gamma_{im}^{(E)}$			Markets sorted by $\beta_{im}^{(HW)}$ and by $\gamma_{im}^{(HW)}$		
	$\beta_{im}^{(E)}$	$\gamma_{im}^{(E)}$	Return	$\beta_{im}^{(HW)}$	$\gamma_{im}^{(HW)}$	Return
P1	0.8000	0.7562	0.5857	0.4431 (0.4518)	0.5213 (0.5290)	0.6558 (0.5722)
P2	1.2705	1.3166	0.4148	0.9706 (0.9967)	1.1469 (1.1675)	0.5347 (0.6182)
P3	1.8463	1.8849	0.9213	1.4709 (1.4835)	1.7146 (1.7252)	0.7520 (0.7520)
Spread (P3-P1)	1.0463	1.1287	0.3356	1.0278 (1.0316)	1.1933 (1.1962)	0.0963 (0.1798)

Notes: P1 consist of the markets that has the lowest nine estimates and P3 consist of the markets that has the highest nine estimates. All entries are arithmetic averages. The risk measures are based on log returns, market portfolio return is the world index return and the risk-free rate is the US 10-year bond rate. The figures in parentheses are the estimates when the risk-free rate in the Hogan and Warren downside beta and downside gamma (equations (4) and (5)) is replaced with the corresponding mean.

Table 5. Portfolio (log) return and risk in sample period Jan 1995 – Dec 2004

Portfolio	Markets sorted by β		Markets sorted by $\beta_{im}^{(E)}$		Markets sorted by $\beta_{im}^{(HW)}$	
	β	Return	$\beta_{im}^{(E)}$	Return	$\beta_{im}^{(HW)}$	Return
P1	0.4195	0.3678	0.8074	0.3678	0.7522	0.3819
P2	1.0419	-0.1522	1.2843	-0.1472	1.3134	-0.1984
P3	1.6403	0.4268	1.9129	0.4218	1.9852	0.4589
Spread (P3-P1)	1.2208	0.0590	1.1055	0.0540	1.2330	0.0770

Portfolio	Markets sorted by $\beta_{im}^{(E)}$ and by $\gamma_{im}^{(E)}$			Markets sorted by $\beta_{im}^{(HW)}$ and by $\gamma_{im}^{(HW)}$		
	$\beta_{im}^{(E)}$	$\gamma_{im}^{(E)}$	Return	$\beta_{im}^{(HW)}$	$\gamma_{im}^{(HW)}$	Return
P1	0.7717	0.7175	0.3678	0.4858	0.5088	0.3678
P2	1.2433	1.2926	-0.1472	1.1654	1.3099	-0.1522
P3	1.7833	1.8293	0.4218	1.6291	1.7540	0.4268
Spread (P3-P1)	1.0116	1.1118	0.0540	1.1433	1.2453	0.0590

Notes: P1 is made up of markets that have the lowest nine risk estimates and P3 is the one with the highest nine estimates. The risk measures are based on log returns, market portfolio return is the world index return and the risk-free rate is the US 10-year bond rate.

Table 6. Cross-sectional analysis of pricing models using arithmetic return

Model	λ_0	λ_1	λ_2
Model A: $R_{it} = \lambda_0 + \lambda_1 \beta_i + \varepsilon_{it}$			R-square = 0.3293
Mean	0.4766	0.9827	-
Standard error	0.2711	0.2805	-
t-value	1.7518***	3.5038*	-
Model B: $R_{it} = \lambda_0 + \lambda_1 \beta_{im}^{(E)} + \varepsilon_{it}$			R-square = 0.5435
Mean	-0.2621	1.2319	-
Standard error	0.3077	0.2258	-
t-value	-0.8521	5.4555*	-
Model C: $R_{it} = \lambda_0 + \lambda_1 \beta_{im}^{(E)} + \lambda_2 \gamma_{im}^{(E)} + \varepsilon_{it}$			Adjusted R-square = 0.5055
Mean	-0.2564	1.1487	0.0803
Standard error	0.3261	1.2896	1.2242
t-value	-0.7861	0.8907	0.0656
Model D: $R_{it} = \lambda_0 + \lambda_1 \beta_{im}^{(HW)} + \varepsilon_{it}$			R-square = 0.1768 (0.2802)
Mean	0.6581 (0.4783)	0.8021 (0.9429)	-
Standard error	0.3171 (0.2991)	0.3462 (0.3023)	-
t-value	2.0752** (1.5991)	2.3168** (3.1193*)	-
Model E: $R_{it} = \lambda_0 + \lambda_1 \beta_{im}^{(HW)} + \lambda_2 \gamma_{im}^{(HW)} + \varepsilon_{it}$			Adjusted R-square = 0.4178 (0.4064)
Mean	0.4468 (0.3742)	-3.0869 (-2.5775)	3.4812 (3.1430)
Standard error	0.2681 (0.2690)	1.1253 (1.3111)	0.9743 (1.1456)
t-value	1.6667*** (1.3909)	-2.7432* (-1.9659**)	3.5729* (2.7435*)
Model F: $R_{it} = \lambda_0 + \lambda_1 \beta_{im}^{(E)} + \lambda_2 \beta_{im}^{(HW)} + \varepsilon_{it}$			Adjusted R-square = 0.6600 (0.6528)
Mean	-0.4320 (-0.6135)	2.2278 (2.6510)	-1.3461 (-1.6492)
Standard error	0.2654 (0.2852)	0.3569 (0.4848)	0.4075 (0.5168)
t-value	-1.6278 (-2.1510**)	6.2418* (5.4681*)	-3.3035* (-3.1911*)

Notes: The statistics are based on 27 estimates. The mean and standard error is expressed as a percentage. *** denotes significance at the 10 percent level, ** denotes significance at the 5 percent level and * denotes significance at the 1 percent level. The figures in parentheses are the estimates when the risk-free rate in the Hogan and Warren downside beta and downside co-skew (equations (4) and (5)) are replaced with the appropriate means.

Table 7. Portfolio (arithmetic) return and risk

Portfolio	Markets sorted by β		Markets sorted by $\beta_{im}^{(E)}$		Markets sorted by $\beta_{im}^{(HW)}$	
	β	Return	$\beta_{im}^{(E)}$	Return	$\beta_{im}^{(HW)}$	Return
P1	0.3677	1.0711	0.8082	0.9511	0.3711 (0.3948)	1.1348 (0.9511)
P2	0.8613	1.0837	1.2543	0.9471	0.8361 (0.9436)	1.3076 (1.2036)
P3	1.3398	1.7991	1.7854	2.0557	1.2610 (1.3332)	1.5114 (1.7991)
Spread (P3-P1)	0.9721	0.7281	0.9772	1.1045	0.8899 (0.9384)	0.3766 (0.8480)

Portfolio	Markets sorted by $\beta_{im}^{(E)}$ and by $\gamma_{im}^{D(E)}$			Markets sorted by $\beta_{im}^{(HW)}$ and by $\gamma_{im}^{(HW)}$		
	$\beta_{im}^{(E)}$	$\gamma_{im}^{D(E)}$	Return	$\beta_{im}^{(HW)}$	$\gamma_{im}^{(HW)}$	Return
P1	0.8082	0.7516	0.9511	0.3711 (0.3948)	0.4803 (0.4742)	1.1462 (1.0138)
P2	1.2543	1.2616	0.9471	0.8361 (0.9436)	1.0611 (1.1217)	1.3311 (1.2978)
P3	1.7854	1.7589	2.0557	1.2610 (1.3332)	1.3980 (1.4959)	1.5745 (1.7608)
Spread (P3-P1)	0.9772	1.0072	1.1045	0.8899 (0.9384)	0.9177 (1.0216)	0.4283 (0.7470)

Notes: P1 is made up of markets that have the lowest nine estimates and P3 is the one with the highest nine estimates. All entries are averages based on nine values. The risk measures are based on arithmetic returns, market portfolio return is the world index return and the risk-free rate is the US 10-year bond rate. The figures in parentheses are the estimates when the risk-free rate in the Hogan and Warren downside beta and downside gamma (equations (4) and (5)) is replaced with the corresponding mean.

Table 8. Cross-sectional analysis with orthogonalised components

Model	λ_0	λ_1	λ_2	λ_3
$R_{it} = \lambda_0 + \lambda_1\beta_i + \lambda_2 O\beta_i^{(E)} + \varepsilon_{it}$			Adjusted R-square = 0.0540	
Mean	0.3206	0.3630	0.4904	-
Standard error	0.2242	0.2249	0.5229	-
t-value	1.4298	1.6140	0.9377	-
$R_{it} = \lambda_0 + \lambda_1\beta_i + \lambda_2 O\beta_i^{(HW)} + \varepsilon_{it}$			Adjusted R-square = 0.2374 (0.0594)	
Mean	0.3206 (0.3206)	0.3630 (0.3630)	-2.2814 (-0.9297)	-
Standard error	0.2013 (0.2236)	0.2019 (0.2243)	0.8708 (0.9192)	-
t-value	1.5925 (1.4339)	1.7976*** (1.619)	-2.6198* (-1.011)	-
$R_{it} = \lambda_0 + \lambda_1\beta_i + \lambda_2\beta_i^{(HW)} + \lambda_3 O\gamma_i^{(HW)} + \varepsilon_{it}$			Adjusted R-square = 0.4233 (0.1990)	
Mean	0.5029 (0.3989)	2.6445 (1.3049)	-2.2814 (-0.9297)	1.9854 (1.9035)
Standard error	0.1852 (0.2183)	0.7774 (0.8840)	0.7573 (0.8483)	0.6717 (0.8362)
t-value	2.7149*(1.8268***)	3.4016* (1.4761)	-3.0126* (-1.096)	2.9557* (2.276**)

Notes: $O\beta_i^{(E)}$, $O\beta_i^{(HW)}$ and $O\gamma_i^{(HW)}$ are the orthogonalised component of the E-beta, the HW-beta and HW-gamma respectively. The mean and standard error is expressed as a percentage. *** denotes significance at the 10 percent level, ** denotes significance at the 5 percent level and * denotes significance at the 1 percent level. The figures in parentheses are the estimates when the risk-free rate in the Hogan and Warren downside beta (equation (4)) is replaced with the corresponding mean.